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1st International Congress on Biosystems Engineering 2019 **ARAŞTIRMA MAKALESİ/RESEARCH ARTICLE**

The use of universal kriging interpolation technique to determine groundwater levels in dry and wet years: A case study in a semi-arid region of Mahdia in Tunisia

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Ö Z E T / A B S T R A C T

Aims: Overexploitation of groundwater (GW) resources leads to lowering of the water table and widespread shallow groundwater contamination, particularly in semi-arid and arid regions of the world. The region of Mahdia, located in the Sahel of Tunisia, is a semi-arid region characterized by its limited surface water and groundwater resources. Overexploitation of groundwater in some shallow aquifers has been detected lately in the region due to the increase of population and human activities. This study aimed to figure out spatial and temporal changes in groundwater elevations through using geostatistical techniques.

Methods and Results: In line with the determined objective, data from 102 groundwater observation wells, located in the Mahdia region in Tunisia, were used in this study. The Regional Commissariat for Agricultural Development of Mahdia (CRDA) provided us with the data of groundwater depth observations from 2005 to 2017, surface elevation and coordinates of the groundwater wells. The use of universal kriging, i.e. “kriging with a drift”, method allowed us to make reasonable interpretations on groundwater levels in dry and wet years. Generated maps by Jeostat Software® demonstrated that the relief of the catchment determines the groundwater divide, which controls hydrological processes in groundwater catchments. In addition, generating groundwater elevation maps for dry and wet years was subtracted and a new map was derived, i.e. difference map. Difference map indicated that overexploitation was accentuated in dry years.

Conclusions: The “universal kriging” method allowed us to obtain groundwater elevation contours and to detect groundwater-depleted areas.

Significance and Impact of the Study: Policies and economic instruments should be taken urgently to manage these overexploited aquifers and recreate the groundwater natural level particularly in dry years.

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INTRODUCTION

Quantification of the groundwater depletion is of capital importance in order to provide information for effective groundwater resources management (Zhou et al., 2013). Groundwater depletion can be detected by integrating the changes of groundwater elevation contour maps over the aquifer area or by using calibrated groundwater models (McGuire et al., 2003). In this regard, geostatistical tools have been widely applied in the sciences of hydrological, environmental, earth, agricultural, etc. to estimate the spatiotemporal variability of data with environmental and economic importance (Christakos, 2000). Geostatistical tools help to characterize and interpret the spatial behavior of existing sample data and to use that interpretation to predict likely values at the locations, which have not been sampled (Clark and Harper, 2000). The most frequently used technique for spatial interpolation is *Ordinary Kriging (OK)*. Simple and ordinary kriging are techniques of *stationary geostatistics*. Nevertheless, in reality, the mean value of some spatial data varies and depends on the absolute location of the sample. This spatial behavior indicates that the variable under investigation is non-stationary. Gundogdu and Guney (2007), Kumar (2007) and Cay and Uyan (2009) used the technique of universal kriging in preference to *OK* to elaborate spatial and temporal analysis of groundwater levels in their studies. Additionally, Gunarathna et al. (2016) pointed out that the lowest root mean square error (RMSE) value for mapping groundwater level in dry season with reference to land surface datum was given by the *Universal Kriging* (*UK*) method. In *UK* practice, the drift is taken into account by introducing *n* drift functions, which are functions of the x and y coordinates. In doing so, the *UK* helps us to increase remarkably the overall reliability of estimates at unsampled locations. The stable objective of this study was to figure out spatial and temporal changes in groundwater elevations through using non-stationary geostatistical techniques.

MATERIAL and METHODS

Groundwater and Precipitation Data and Pre-processing of Data for Analysis

In the present work, *Universal Kriging (UK)* is used to interpolate groundwater level data of Mahdia shallow aquifers at the central of Tunisia located between 10°-11° north parallels, and the 35° east meridian. The aquifer system covers an area of 2878 km^2 and the available data consist of 102 hydraulic head measurements that are randomly distributed over this area. Data of annual rainfall from 1980 to 2017 were statistically analyzed; annual rainfall data followed normal distribution (Fig. 1). Wet and dry years (from 2005 to 2017) were determined by using *standardized precipitation index (SPI, i.e. z-value) method* following the procedure given in Keskiner et al. (2019)*;* and so z-values were calculated. Any given year with negative z-value was classified as a "*dry year*" and a year with positive z-value was classified as a *"wet year*" (Table 1). This classification is useful to estimate and compare the groundwater elevation, based on mean sea level in meters, in *dry* and *wet* years. Elevation of groundwater was calculated as the surface elevation of observation well minus the depth of water table as explained in Cetin and Diker (2003).

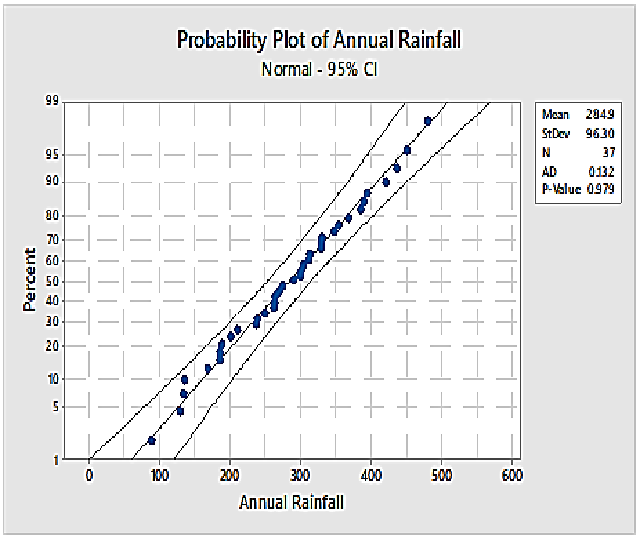


Fig. 1. Distribution of annual rainfall data

Table 1. Classification of years

Annual Rainfall (mm)	Probability	Z_Value	Years
305.12	0.58	0.21	2005
291.04	0.52	0.06	2006
329.95	0.67	0.47	2007
262.40	0.40	-0.23	2008
367.94	0.80	0.86	2009
264.20	0.41	-0.22	2010
249.69	0.35	-0.37	2011
330.55	0.68	0.47	2012
134.30	0.05	-1.56	2013
394.90	0.87	1.14	2014
330.00	0.68	0.47	2015
263.60	0.41	-0.22	2016
436.52	0.94	1.57	2017

Semivariogram Analysis and Models

One of the basic geostatistical tools used for spatial estimation is the semivariogram, i.e. *γ(h)*. It represents variation in the value of the parameters observed as a function of the distance between the points in which these observations were made. Modelling a semivariogram is an important step in the geostatistical analysis. Modeling of a semivariogram involves fitting a suitable theoretical semivariogram model to experimental values (Pannatier, 1996; Cetin and Kirda, 2003). A number of candidate theoretical semivariogram models were used in this work to better describe the shape of the experimental semivariograms. The most

$$\gamma(|h|)= C_o+C_1\, Gauss_a(|h|)= C_o+C_1 \left[1 - e^{-3\frac{|h^2|}{a^2}}\right] \qquad \text{(Eq. 1)}$$

$$\gamma(|h|)= C_o+C_1\, sph_a(|h|)= \begin{cases} C_0 + C_1\left[1.5\,\frac{|h|}{R} - 0.5\,\left(\frac{|h|}{R}\right)^3\right], & \text{if } |h| \leq R \\ C & , otherwise \end{cases} \qquad \text{(Eq. 2)}$$

$$g^*_{icubic}(x,y) = \alpha_0+\alpha_1 x + \alpha_2 Y+\alpha_3 xy + \alpha_4 x^2 + \alpha_5 y^2+ \alpha_6 x^2y+ \alpha_7 xy^2+ \alpha_8 x^3+ \alpha_9 x^3 \qquad \text{(Eq. 3)}$$

commonly used ones (Cetin and Kirda, 2003) were given Eq. 1. Gaussian model with nugget effect.
Where; *a:* Practical range of influence (in the unit of distance), *h:* Separation distance between sample pairs (in the unit of distance), *C:* The sill value of semivariogram, consisting of nugget (C_o) and stochastic (C_1) variance, i.e. $C=C_o+C_1$. Spherical model with nugget effect.

Detrending and Kriging Estimations

In non-stationary geostatistics, i.e. when the semivariogram has not a stable sill, then, removing the trend component ($g^*_i(x,y)$) from the observed, or original data (g_i) is a prerequisite. This is done by subtracting the value of trend surface from observations, i.e. g_is. Finally, trend-free data (g_{ires} *(x,y)*) were obtained as explained below. Vieira et al. (2010) mentioned that the method of removing the trend consist of fitting three-dimensional surface to the data by the least squares and subtracting its values from the original g_is. The degree of the trend surface is determined by conducting analysis of variance (ANOVA), i.e. comparison of F_{values} with F_{table} (Clark and Harper, 2000). The cubic trend surface model might be expressed mathematically as the following Eq. 2.
where; *x, y*: Universal Transverse Mercator (UTM) coordinates (in the unit of distance), α_i: Regression coefficients.

$$g_{ires}(x,y) = g_i - g^*_{icubic}(x,y) \qquad \text{(Eq. 4)}$$

The trend model and its parameters (Eq. 3) are determined by conducting ANOVA, then, trend component (or drift) in observed data is removed by using Eq. 4. If de-trending is done accordingly, residuals are supposed to show characteristics of stationary data. If it comes to that, the next step is to determine a suitable theoretical semi-variogram model to experimental semivariogram of residuals, i.e. $g_{ires}(x,y)$, obtained by Eq. 4. Then, kriging estimates of residuals $[\hat{g}_{ires}(x,y)]$ are made by solving the kriging system of equations (Cetin and Kirda, 2003) at the grid nodes established over the study area. Finally, the likely value at any unsampled location, or *grid node* over the study area is estimated as the following.

$$\hat{g}_i(x,y) = \hat{g}_{ires}(x,y) + g^*_{icubic}(x,y) \qquad \text{(Eq. 5)}$$

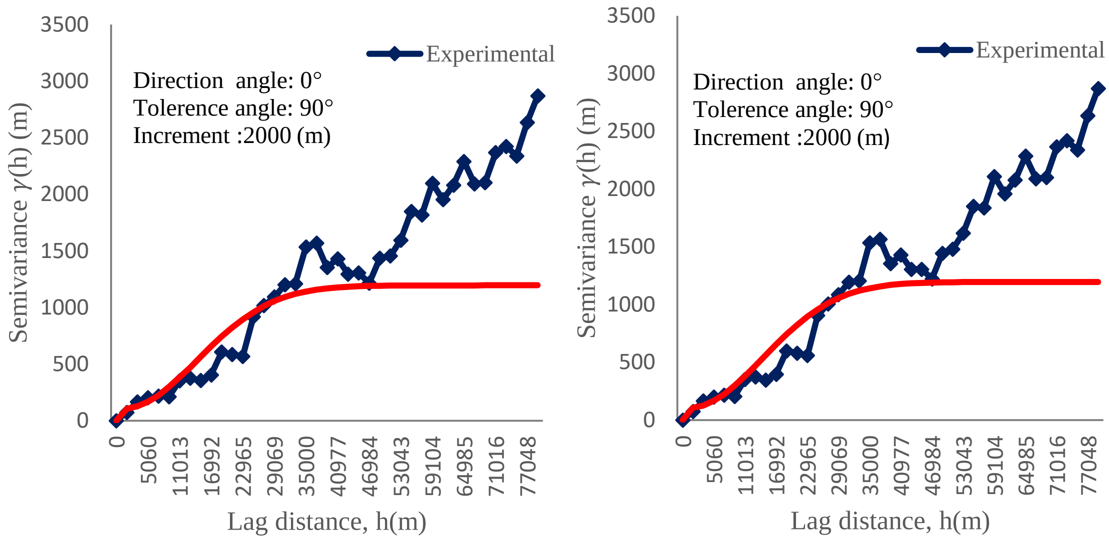
where *i* stands for the grid node number. This method is called as "*Universal Kriging (UK)*" or *kriging with drift* (Wackernagel, 2003) and (Menafoglio and Secchi, 2013).

RESULTS and DISCUSSION

Semivariogram Models and Estimated Parameters

In this study, "J*eostat*" software developed by Mert and Dag (2017) was used to identify the most reliable theoretical semivariogram models for the groundwater variables examined. For dry and wet years, the "*Gaussian model*" is found as the most consistent model. Cressie goodness of fit statistics indicated a good fit to the observed data (0.053 for wet years and 0.057 for dry years). Experimental semivariograms were obtained by setting the direction angle to 0.0 degrees and tolerance angle to ±90 degrees. Therefore, omnidirectional experimental semivariograms were obtained for the data. Results were visually depicted in Fig. 2. Additionally, Table 2 indicates the model parameters. It is important to address that semivariograms contained the nugget effect (C_0) which was unusually small. However, having this parameter is an implication of spatial variability at the distances shorter than the minimum sampling distance and other unaccountable experimental measurements errors. In our case, the minimum sampling distance was about 2000 m. The share of stochastic variance (C_1) in sill value (C) was almost the same for the data of dry and wet years, 91.63% and 91.68 %, respectively. However, the range of influence, i.e. *a,* was a bit higher in wet years (37.3 km) than dry years (35 km).
Experimental semivariograms are the mirror of the spatial behavior of the data in the hand. As seen in the

Fig. 2, they show clearly that there is a significant trend in the values on the larger scale, indicating groundwater elevations are non-stationary.



(a) **(b)**

Fig. 2. Theoretical (solid lines) and experimental (smooth lines with markers) semivariograms of the observed (original) groundwater (GW) level data: (a) dry, (b) wet years

Table 2. Gaussian semivariogram model parameters of groundwater elevation data

Variable [GW elevation]	**C_0**	**C_1**	**C**	**$(C_1/C)*100$**	***a***
Dry years Residuals	100	1095.92	1195.92	91.63	34990.47
Wet years Residuals	100	1102.26	1202.26	91.68	37317.86

C_0: Nugget variance; C_1Stochastic component; *C*: Sill value (m); *a*: Practical range of influence (m)

Table 3. Analyses of variance of dry years' data for modelling trend

Trend model	**Sum of squares**	**Degrees of freedom**	**Mean square**	**F ratio**
Linear	74684.83	2	37342.41	80.48
Linear residuals	45930.45	99	463.94	
Quadratic	92699.68	5	18539.93	63.75
Diff (linear and quadratic)	18014.84	3	6004.94	20.65
Quadratic residuals	27915.60	96	290.78	
Partial cubic	92743.06	6	15457.17	52.68
Diff (quadratic and cubic)	43.38	1	43.38	0.14
Partial cubic residuals	27872.22	95	293.39	
Total variation	120615.29	101	1194.21	

Trend Surface Analysis

The method used to justify the sustainability of least squares fit is the Analyses of Variance, i.e. ANOVA in conventional statistics. ANOVA test for determining the degree of drift functions is valid only if residuals are normally distributed. Keeping this in mind, trend surface analysis was done accordingly and ANOVA results were summarized in the Tables 3-5. By comparing the last column "*F ratio*" with *F table* at various significance levels, it was concluded that linear and quadratic trend functions were significantly different, indicating that quadratic trend is better than linear one. As seen in the Tables 3-4, *F* value for difference between quadratic and linear trend model is statistically significant which means that significant proportion of the variation in the data has been explained by the quadratic trend. Nevertheless, partial cubic trend is not significant (*F ratio*

= 0.14< *F table* for dry years; *F ratio* = 0.11< *F table* for wet years) (Table 3-4) at the 95% probability (α=5%). ANOVA analysis results led us to conclude that the quadratic trend with the coefficients given in the Table 5 might be used confidently in UK estimates of GW elevations in the region of Mahdia.

Table 4. Analyses of variance of wet years groundwater elevations data for modelling trend

Trend model	Sum of squares	Degrees of freedom	Mean square	F ratio
Linear	74979.37	2	37489.68	81.63
Linear residuals	45462.09	99	459.21	
Quadratic	93084.62	5	18616.92	65.33
Diff (linear and quadratic)	18105.24	3	6035.08	21.17
Quadratic residuals	27356.84	96	284.96	
Partial cubic	93116.94	6	15519.49	53.95
Diff (quadratic and cubic)	32.32	1	32.32	0.11
Partial cubic residuals	27324.52	95	287.62	
Total variation	120441.47	101	1192.48	

Table 5. Analyses of variance of wet years groundwater elevations data for modelling trend

Climatic conditions	α0	α_1	α_2	α_3	α_4	α_5
Dry years	-476389.23	-0.03	0.25	1.56E-08	-2.10216E-08	-3.33676E-08
Wet years	-478374.50	-0.03	0.25	1.54E-08	-2.11035E-08	-3.34652E-08

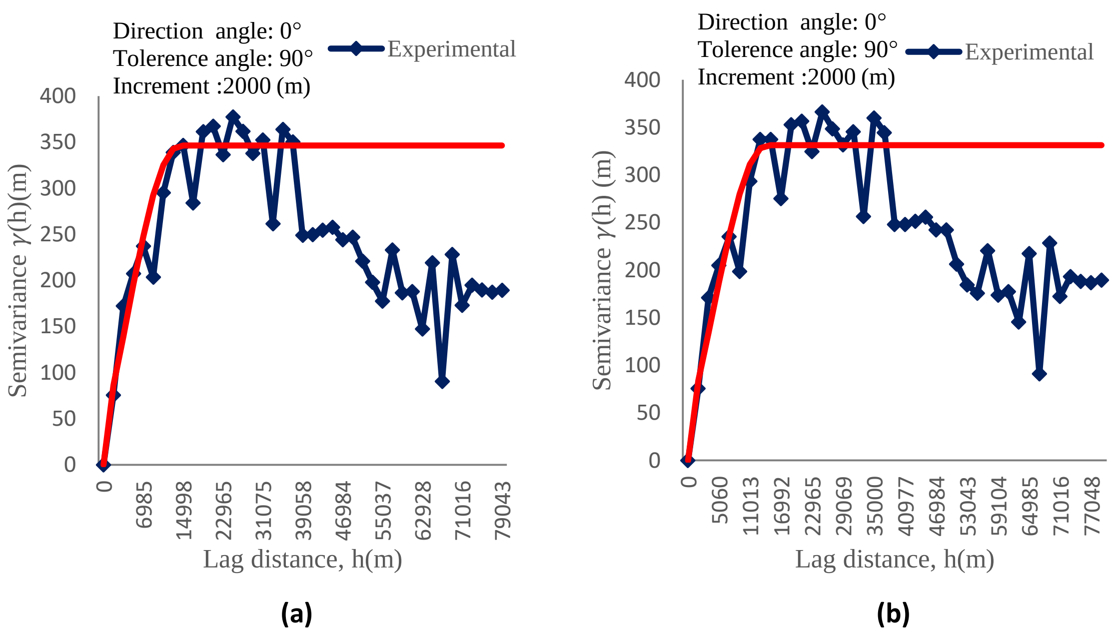


Fig. 3. Experimental semivariograms for the detrended GW elevations of Mahdia's aquifer: (a) dry, (b) wet years

Table 6. Theoretical semivariogram models and parameters of detrended groundwater elevations (residuals)

Climatic conditions	C_0	C_1	C	$(C_1/C)*100$	*a*
Detrended data for *dry* years	36.43	309.71	346.14	89.47	14145
Detrended data for *wet* years	36.62	294.7	331.32	88.94	14145

Semivariogram Analysis for the Detrended Data

Trend component in the *GW* elevation data was removed by employing Equation 4 for 102-observation points. In this regard, *UTM* coordinates of *GW* wells were used in the trend estimation. After removing the influence of the drift in *GW* elevations, *"Jeostat"* software was used to identify omnidirectional experimental semivariograms, and to expose the most reliable theoretical models. Finally, based on the visual examination of experimental semivariograms, it was postulated that "*spherical model*" containing all possible pairs in all possible directions was the most appropriate theoretical model for dry and wet years. Cressie goodness of fit statistics of 0.069 for dry years and 0.015 for wet years proved our postulation based on the evidence of visually good fit to the experimental data as seen in the Fig. 3. Spherical semivariogram parameters (C_0, C_1, R) were defined and given in Table 6. As seen in Fig. 3, the quadratic trend model is well enough to remove drift in the GW elevation data regardless of whether data belong to wet or dry years. Furthermore, the variance structure of detrended groundwater elevation is similar in dry and wet years.

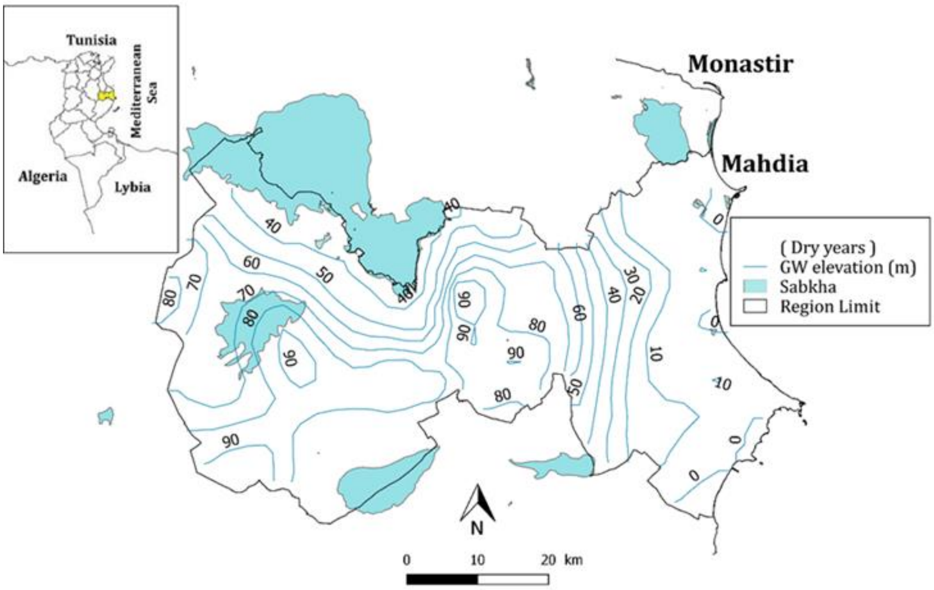


Fig. 4. Groundwater elevation in dry years

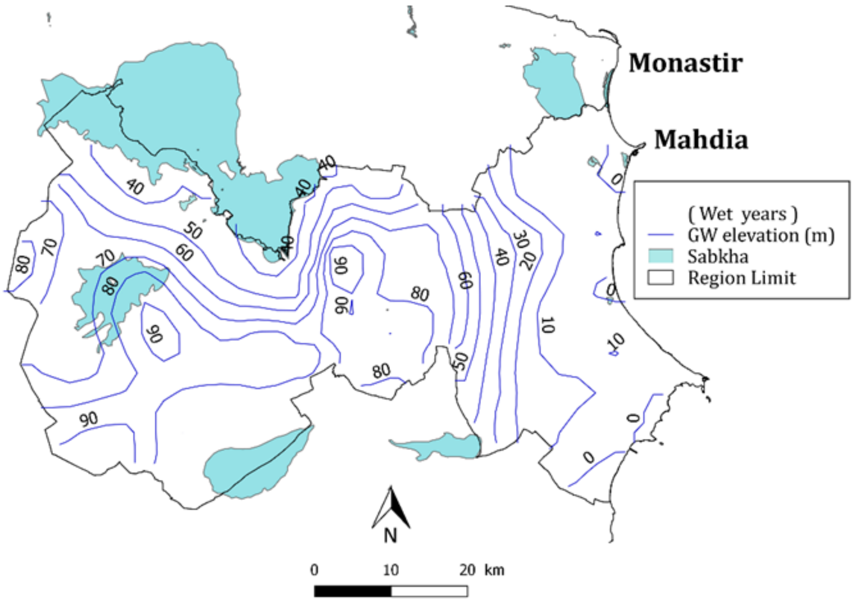


Fig. 5. Groundwater elevation in wet years

Generated Contours of Groundwater Elevation

The most important output of geostatistical studies are *kriging estimation* (*KE*) and *kriging error (KSD)* maps. In this study, the *"jeostat"* program was used to make kriging estimates of residuals, i.e. detrended *GW* elevations. To this end, study area was gridded consisting of 630 points/cells (18 rows and 35 columns) with the size of 2.5 km by 2.5 km. Residuals $\{\hat{g}_{ires}(x, y)\}$ and trend $\{g^*_{iquadratic}(x, y)\}$ components were estimated by *OK* technique and Eq. 3, respectively, for each grid node. Then, Eq. 5 was used to obtain the likely groundwater elevation at each grid node for dry and wet years. Generated groundwater elevation maps were presented in Fig. 4 for *dry* years and Fig. 5 for *wet* years. Yao et al. (2015) concluded in their study that groundwater levels correlated with topographic elevation. Fig 4 and Fig. 5 showed that the highest groundwater elevations are located in the central parts and in the south west of the region, which follow the surface topographic elevation of the region of Mahdia. Additionally, generated *GW* elevation maps show clearly that groundwater discharges either into *sabkhas (Sidi El Hani, Cherita etc.)* or directly to the Mediterranean Sea. Local information proved that generated groundwater elevation maps were in harmony with the hydraulic conditions in the region, indicating that the methodology applied was successful to simulate *GW* dynamics in region of Mahdia.

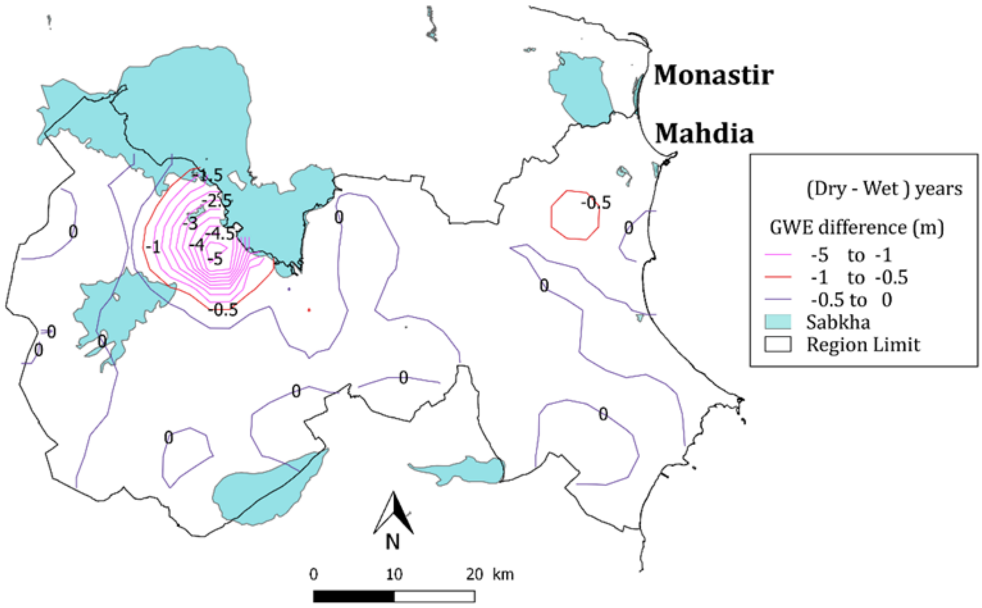


Fig. 6. The difference in groundwater elevation between dry and wet years

Fig. 6 was generated by subtracting Fig 4 and Fig. 5. It shows the diminution of groundwater elevation in dry years comparing by wet years in the majority of the region. Nevertheless, overexploitation is accentuated only in two locations in dry years: in Mahdia-ksouressef aquifer and in the areas located between Souassi and Sidi el Hani Shallow aquifers. Groundwater elevation diminished from 0.5 m to 1 m in Mahdia-ksouressef aquifer, and from 0.5 m to 5 m between Souassi and Sidi el Hani Shallow aquifers. This overexploitation is explained by the presence of private irrigation perimeters in these areas and the excessive and uncontrolled extraction of groundwater. This is a good indication of overstress caused by anthropogenic factors such as agriculture, tourism, etc. on groundwater resources in the profound arid regions.

CONCLUSIONS

Groundwater elevations that cannot be directly measured can be objectively simulated by utilizing geostatistical tools. Experimental semivariograms may be used to figure out whether data are stationary or not. Stationary and non-stationary kriging estimates might be helpful for the groundwater managers and practitioners in the field, particularly in the region of Mahdia, in order to prepare sensible groundwater management plans for ensuring sustainability of groundwater resources. The method of "*universal kriging*", i.e. *UK*, was shown its efficiency to obtain the contours of groundwater elevation in wet and dry years. Some areas (private irrigation perimeters) showed high depletion in groundwater elevations in dry years. Thus, policy and measurements should be taken urgently in these areas to maintain the suitability of shallow aquifers in the region of Mahdia.

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DECLARATION OF CONFLICTING INTERESTS

The author(s) declare no conflict of interest for this study.

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